

Detection of Characteristic Points in ECG Using a MART

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This study proposes a new method for detecting characteristic points (CPs), the Q and S points, in electrocardiogram (ECG) using a multichannel ART-based neural network (MART). The method integrates the previous two methods: the slope detection techniques and neural networks. The slope detection techniques are able to locate CPs exactly. However, it is not robust to noise. On the other hand, the method of neural networks locates approximate locations of the CPs and self-organizes in response to newly input patterns. This self-organizing ability makes the method robust. The MART integrates these two methods to implement a reliable CPs detection. For the CPs detection, ECG is divided into cardiac cycles by preprocessor, and each cardiac cycles is input to the channel one of the MART. A rectangle is made from each cardiac cycle and input to channel two of the MART. Patterns of the two channels are transmitted to the F3 layer of the MART, and then the winner node of the F3 layer recalls template patterns to the channels in the F1 layer. When the pattern recognition carried out by the MART, the template locates CPs in the ECG. The method were evaluated using MIT/BIH arrhythmia database. The standards deviation between detected CPs and CPs estimated by referee are within the limit of the SDs recommended by the CSE committee.

Keywords: electrocardiogram, characteristic point, neural networks

1. Introduction

Electrocardiogram (ECG) can be measured easily and noninvasively by attaching small electrodes to our body, and the ECG has been used as a standard tool to diagnose heart diseases⁽¹⁾⁽²⁾. A typical ECG is illustrated in Fig. 1. For precise diagnosis, the ECG is recorded for a whole day with a Holter device which records ECGs of 100,000 cardiac cycles per subject. A physician interprets this large amount of ECGs to search for a few abnormal cardiac cycles. This is tedious routine for a physician and overlook would be induced by mental fatigue. From this background, computerized analyzer to interpret the ECG has been developed.

The most popular computerized ECG analyzer is a beat-to-beat analyzer^{(3)~(7)}. It locates QRS complex in the ECG, and calculates their duration. The QRS complex is located by detecting signal of the ECG between the onset and offset of the QRS complex. Moreover, studies on locating P and T waves have been carried out to calculate interwave segment. These are studies to locate waves in the ECG. However, it is necessary to analyze patterns of waves in the ECG to realize advanced computerized analyzer. To analyze waves in the ECG, we have to segment a piece of wave in ECG. For the segmentation, it is required to detect characteristic points (CPs) that are onset and offset of the waves. In the computerized ECG analyzer, an erroneous diagnosis happen from both measurement error of the ECG and detection error of its CPs. Since detection error

of the CPs causes the most erroneous diagnosis, precise detection of CPs is necessary to make a computerized ECG analyzer more reliable. The QRS wave is a reference wave used to detect other waves, therefore we will propose the method for detecting the Q and S points to pick up the QRS wave for the first step to implement a reliable ECG analyzer in this paper.

The prevailing method to detect the Q and S points are slope detection techniques in which the Q and S points are located to detect the QRS-wave by examining either a change in the sign of the slope of the ECG, zero slope, or significant change in the slope within the search region⁽⁸⁾. The search region is determined based on physiological knowledge. This method is not robust to noise. Another method of detecting the QRS-wave is the syntactic method⁽⁹⁾⁽¹⁰⁾. This method based on the assumption that the ECG is composed of peaks and segments, which are primitives to constitute the ECG. Primitive selection is both problem- and pattern-dependent and there is no general solution to this problem. Sahambi and other researchers proposed a method detecting the CPs using Wavelet transform (WT)⁽¹¹⁾⁽¹²⁾. Basically, the WT comprises a convolution of the input signal with a modulated pulsation to provide a time-frequency distribution. Since the amount of the computation needed to implement these techniques, it is not able to detect the CPs within real time processing. Therefore, this method is not useful for real-time monitor of patients in the coronary care unit and to monitor patients living in their homes. Moreover,

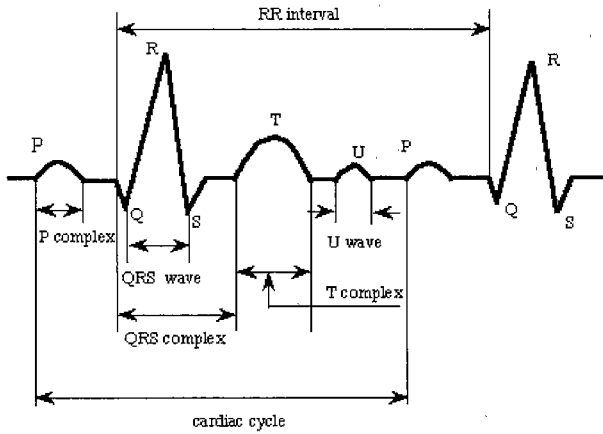


Fig. 1. A cardiac cycle of an ECG. The ECG are divided into waves and complexes by the CPs such as the Q point, the R point, the S point, the T point, and the U point.

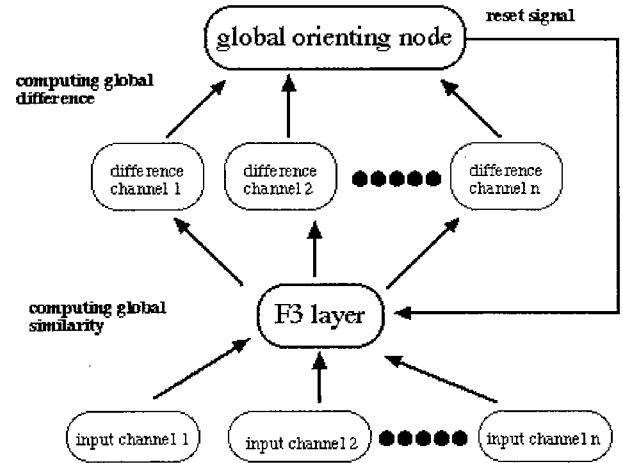


Fig. 2. Block diagram of the MART.

this method cannot distinguish normal ECG from the abnormal ECG which is largely different from normal ECGs by irregular rhythm and/or measurement error. The CPs detection for the abnormal ECGs should be excluded and the abnormal ECG should be classified into the other categories.

We developed a new method for detecting the CPs, the Q and S points, using multichannel ART-based neural network (MART) in this paper⁽¹³⁾. The ART is neural networks model that materializes self-organization of stable category recognition codes for analog input patterns. The ART neural network has learning and self-organizing abilities⁽¹⁴⁾. These abilities are appropriate and make the method robust, because the ECG will change its shape according to the patient's condition⁽¹⁵⁾⁽¹⁶⁾. The method with ART neural network locates approximate locations of the CPs. On the other hand, the slope detection techniques locates the CPs exactly, but it is not robust to noise. Therefore, we integrate two methods, the slope detection techniques and neural network method, using the MART to implement a reliable CPs detection. This method enable self-organization in response to newly input ECG and locates CPs exactly. The self-organizing ability can classify the abnormal ECG into the new category, if the abnormal ECG is largely different from the normal ECG, which should be excluded for the CPs detection. Moreover, since the amount of the computation of the method is negligible for personal computer, the method enables real-time processing and it is applicable to real-time monitor of patients in the coronary care unit and to monitor patients living in their homes.

This paper is organized as follows. Section 2 describes the method to detect the CPs using the MART. Section 3 illustrates the experiments to evaluate the proposed method using MIT/BIH arrhythmia database. In addition, we will report results and provide discussion on the experiments. Finally, the paper will be concluded in section 4.

2. Method to detect CPs

2.1 MART MART is a multichannel neural network and each channel of it consists of ART neural network. Fig. 2 shows a block diagram of the MART. Pattern recognition with MART is divided into two parts; computing global similarity and computing global difference. In computing global similarity, a set of patterns is input to the corresponding channels and associates template patterns stored in each ART network. The template patterns generates signals and they are sent to F3 layer of the MART. A competitive interaction among nodes in F3 layer activates one winner node and the other nodes are inhibited to be inactive. The winner node represents a global similarity to classify the set of input patterns to a specific category.

In computing the global difference d , the winner node that is activated by the set of input patterns associates a set of template patterns to the corresponding difference channels. The template patterns are compared with the set of input patterns. In this sense, d is computed as a difference between a set of input and template patterns. When d is smaller than a global vigilance parameter ρ_g , the current set of input pattern is assigned to the category. Moreover, when d is also smaller than similar criterion ρ_a , the template patterns are modified to get new information of the set of input patterns. This is a self-organization in response to newly input patterns. Both parameter ρ_g and ρ_a are given in advance. The parameter ρ_g is used for pattern recognition, and the parameter ρ_a is used to determine whether learning carried out or not. On the other hand, if d is larger than ρ_g , a reset signal is sent to the F3 layer and the active node is inhibited and new pattern recognition cycle is initiated. The cycle is repeated until either a category is found for which d is smaller than ρ_g or the set of current patterns is assigned to new created category as a set of novel patterns. For the CPs detection, we employed MART with two channels. There are 36 nodes in each channel of F1 and F2 layer, respectively. The number of nodes in F3 layer is the same as the number of nodes in F2 layer.

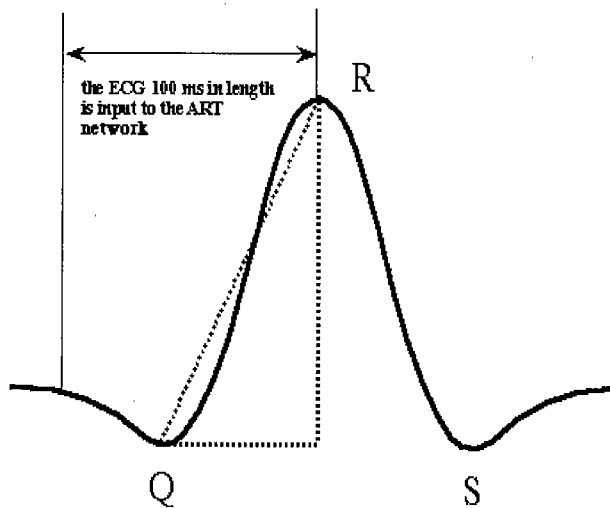


Fig. 3. The principle of pattern recognition with ART network. The solid curve shows a ECG including the QRS-wave. The dotted line is a right-angled triangle pattern to approximate the part of the ECG. The closest right-angled triangle pattern to the part of the ECG will be associated by the ART network.

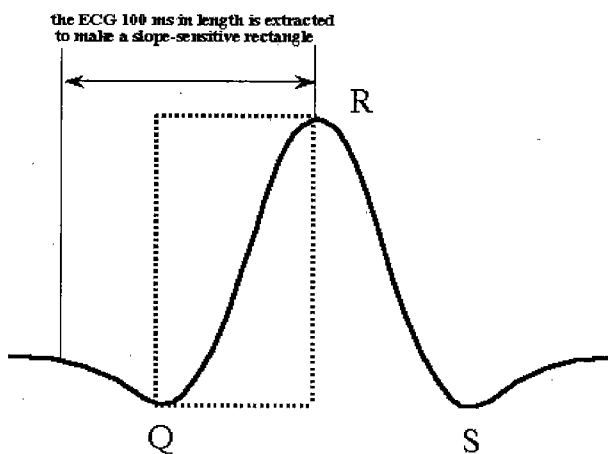


Fig. 4. A slope-sensitive rectangle. The solid curve shows a part of the ECG including the QRS-wave. The dotted line is the slope-sensitive rectangle which is input to the MART.

2.2 Detection of the CPs with MART

We assume that both the parts of the ECG from the R point to the Q point and from the R point to the S point can be approximated by a straight line. We select a well-fitted right-angled triangle for approximating the part of the ECG as shown in Fig. 3, which is employed as a template pattern for the detection of CPs. For the channel one of the MART, 36 right-angled triangle are stored as template patterns in the ART network. The length of the base of each triangle is different.

Before the detection of CPs, the R points of the ECG are detected using the algorithm by Hamilton and Tompkins⁽⁴⁾. The ECG is divided into each cardiac cycle that is a interval of the ECG between R points. For the Q point detection, the part of the ECG 100 ms in

length from the R point in the direction towards the P point (QR part) is input to the channel one. Then the F1 layer of the ART network receives the part of the ECG and sends it to the F2 layer. Each node in F2 layer is activated in proportion to the similarity between the input ECG and the right-angle triangle which is stored between the node in the F2 layer and nodes in the F1 layer. The activated nodes in F2 layer send signals to F3 layer of the MART. For the S point detection, the part of the ECG 100 ms in length from the R point in the direction towards the T point (RS part) is input to the channel one of the MART.

For the channel two of the MART, a slope-sensitive rectangle is input to it as shown in Fig. 4. The height of the rectangle is 1.0 because the amplitude of the ECG was normalized between 0.0 and 1.0. The length of the width is determined from a slope of the ECG. There are two kinds of slope-sensitive rectangles: one is for the Q point detection and the other is for the S point detection. The QR part is extracted to make a slope-sensitive rectangle for the Q point detection. We compute a slope of the ECG from the R point towards the P point. The left end of the bottom side of the rectangle is the location where the condition

$$|ECG(n) - ECG(n - 1)| \leq 0.05$$

$$\text{and } ECG(n) < 0.3 \quad \dots\dots\dots (1)$$

is satisfied. $ECG(n)$ is ECG at the sample location n . The width of the slope-sensitive rectangle is from the R point to the sample location where (1) is satisfied. The slope-sensitive rectangle for the S point detection is determined as the same manner.

In channel two, 36 rectangles are stored in the ART network as template patterns. The length of the bottom side is different and the heights of all them are 1.0. When the slope-sensitive rectangle made from the ECG is input to the channel two, the F1 layer of the ART network of the channel 2 receives the rectangle and nodes in the F1 layer sends signals to the F2 layer. The each node in the F2 layer is activated in proportion to the similarity between the input rectangle and the rectangle being stored in the ART network. The activated nodes in F2 layer send signals to the F3 layer of the MART.

The CPs detection is performed as follows. In the F3 layer, the signals both from the F2 layer of the channel one and the the channel two are integrated to compute the global similarity for the set of input patterns. As in Fig. 2, the activated node associates right-angled triangle to the difference channel one and it also associates a rectangle to the difference channel two. The each associated pattern is compared with each corresponding input pattern, and the difference is summed to compute d . If d is smaller than ρ_g , the set of patterns is classified into a specific category. In this case, the left end of the bottom side of the associated rectangle locates the Q point when the QR part is input to the MART. On the other hand, the right end of the bottom side of the rectangle locates the S point, when the RS part is input

to the ART.

If d is larger than ρ_g , a reset signal is sent to the F3 layer and the pattern recognition does not take place. In this case, the input ECG might be largely different from the previously input ECG by irregular rhythm and/or measuring error. This ECG is classified into different category as an abnormal ECG. By this classification, we can monitor the abnormal ECG.

After the CPs are detected, template pattern $z_{jk^*}(n)$ stored in the channel one are updated by (2). The update is performed when following two conditions are satisfied; $d < \rho_a$ and $d_1 < \rho_g$, where d_1 is difference between template pattern and input ECG in channel one⁽¹³⁾.

$$z_{jk^*}(n+1) = \frac{[A_z z_{jk^*}(n) + A_1 I_j(n)] - m_{k^*}}{M_{k^*} - m_{k^*}} \quad (2)$$

$(j = 1, 2, \dots, 36; k = 1, 2, \dots, 36)$

$$m_{k^*} = \min_l [A_z z_{lk^*}(n) + A_1 I_l(n)] \quad (3)$$

$$M_{k^*} = \max_l [A_z z_{lk^*}(n) + A_1 I_l(n)] \quad \dots \dots \quad (4)$$

$(l = 1, 2, \dots, 36)$

In (2), k^* is the index of the winner node in the F3 layer. $I_j(n)$ is the input signal to the j th node in the F1 layer. A_z and A_1 are parameters of the MART. The parameters for CPs detection are $\rho_g = 0.4$, $\rho_a = 0.1$, $A_1 = 0.75$, and $A_z = 0.25$.

3. Results and discussion

We proposed a new method to detect the CPs, the Q and S points, in the ECG using the MART in this paper. The QRS wave is a reference wave to detect other waves, therefore this is the first step to implement a reliable ECG analyzer. In the method, slope detection techniques and method with neural networks are integrated to bring out advantage points for two methods. However, this method is not a general purpose. It is a specific method to detect CPs. In the slope detection techniques, the ECG signal is transformed to emphasize the QRS wave. Then, the location of the R point is detected to divide the ECG into cardiac cycles. Since the techniques are not robust to noise, the cardiac cycles are stacked one over another to reduce noises. After that, the CPs are detected in the established region that is determined based on the physiological knowledge. The detected CPs are an average of all CPs of cardiac cycles before stacking. The techniques detect exact location of the CP, but they cannot detect the CPs of each cardiac cycle. In the proposed method, we employed a self-organizing neural networks. Learning and self-organizing abilities might be essential to implement a reliable ECG analyzer because shape of the ECG varies with patients slightly and also change with time passage. However, method of neural networks locates approximate locations of the CPs. We bring out

advantage points of the slope detection techniques and neural networks using the MART in this paper.

We evaluated the method to detect the CPs using MIT/BIH arrhythmia database. For precise evaluation, we chose the ECG record number in which we can visually locate the CPs clearly. The ECG record numbers are 100, 101, 103, 105, 109, 111, 112, 113, 115, 116, 117, 119, 122, 123, and 124. Two hundreds cardiac cycles were selected in each record number, and therefore a total of 3000 cardiac cycles were used for the evaluation. For the evaluation, the Q point is define as the first inflection point in the part of ECG from the R point towards the P point⁽¹⁷⁾. The S point is also defined as the first inflection point in the part of the ECG from the R point toward the T point. However, since the ECG is contaminated by noise, these definitions might not be effective for the ECG in practical measurement. To evaluate detected CPs correctly, a part of ECG including the QRS wave was expanded and drawn on a display of a personal computer. A referee found out the locations of the Q and S points visually. This was carried out by examining the slope change of the ECG and the wave form of the ECG before and after the visually found Q and S points. For precise evaluation, if the referee could visually locate the CPs clearly, we calculated the detection error. We considered that the Q and S points located by the referee were the true Q and S points. Examples of detected CPs are illustrated in Fig. 5.

Detection error was computed as

$$S_{error} = n_c - n_v \quad \dots \dots \dots \quad (5)$$

where n_c is the location of the ECG where the CPs is detected by the method and n_v is the location of the ECG where the CPs is located by the referee. This evaluation is more rigorous than evaluation of the method for the previous CPs detection because we performed sampling basis evaluation⁽¹¹⁾⁽¹²⁾. Fig. 6 summarizes results of the evaluation. For the Q point detection, the rate of accuracy with $|S_{error}| \leq 2$ is 86.5% and the rate of accuracy with $|S_{error}| \leq 3$ is 92.3%. For the S point detection, rate of accuracy with $|S_{error}| \leq 2$ is 93.1% and rate of accuracy with $|S_{error}| \leq 3$ is 94.2%.

Table 1 shows the standard deviation (SD) between detected CPs and the true CPs, in which the CPs detection with the MART is compared with that with the ART network. Table 1 also shows the limit of the SD recommended by the CSE committee, which was determined using CSE ECG library⁽¹⁸⁾. The SDs of the MART are within the limit of the SDs for both the Q and S points, however the SD of the ART network falls outside of the limit. Above results justify the potential of our method for detecting the Q and S points.

In pattern recognition, we first make template patterns and then classify input patterns into one of them that is the closest to the input pattern. Robustness of pattern recognition depends on how the template patterns extract the features of the incoming patterns⁽¹⁹⁾. The features of the incoming patterns, however, may change with time and environmental changes surround-

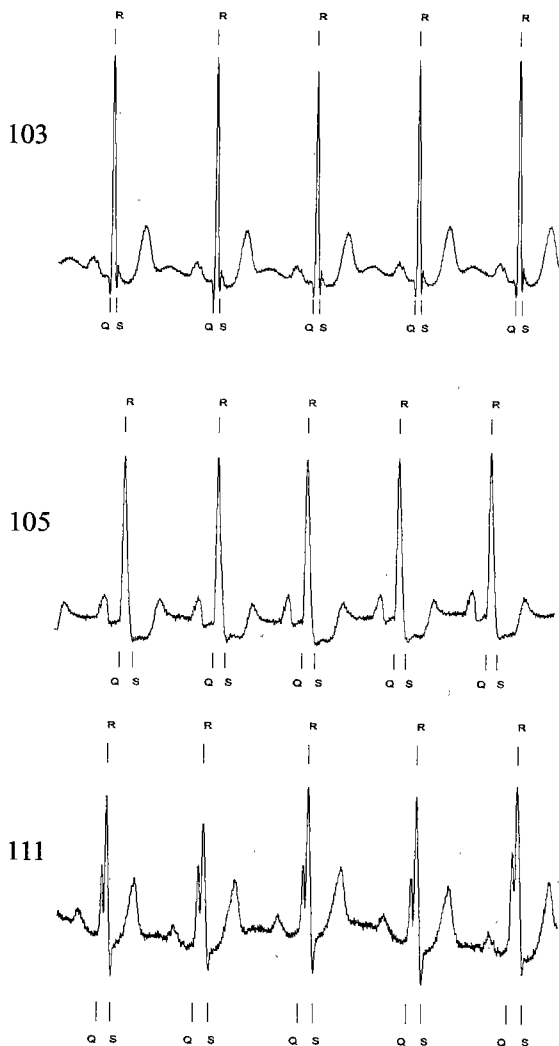


Fig. 5. Examples of the ECGs in which CPs are detected.

Table 1. The standard deviation between detected CPs and the true CPs.

standard deviation	Q point	S point
MART	5.3	4.3
ART	7.6	5.5
slope detection	7.0	6.5
Limit of CSE committee	6.5	11.6

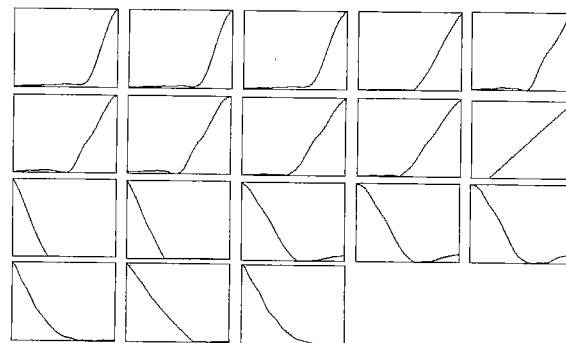


Fig. 7. An example of the stored pattern in the ART network after processing the ECG from record number 109. Upper two line of panels are patterns stored for the Q point detection. Lower line of the panels are patterns stored for the S point detection.

ing the measuring system. Therefore, it is difficult to make template patterns that have all essential features of the patterns incoming in the feature. Especially, a heart changes its cardiac rhythm according to the body's condition, so that the shape of the ECG varies with each patient slightly and changes with time. For these reasons, a self-organizing pattern recognition is needed for CPs detection.

The MART obtains new information from the incoming ECG and self-organizes in response to it. In the initial stage, all the stored patterns in the channel one are right-angled triangle patterns. The right-angled triangle patterns are updated by self-organization as shown in Fig. 7. These patterns are speculated as the dominant feature patterns of the ECGs for a subject. As the process goes on, the channel one of the MART stores many dominant feature patterns, and these patterns are used for more correct pattern recognition. In this manner, the template patterns are updated by the self-organization of the MART in response to the input patterns.

4. Conclusion

We proposed a new method to detect the CPs, the Q and S points, in ECG using MART. The slope detection techniques and self-organizing method by neural networks are integrated to implement a reliable ECG analyzer. Experimental results showed the potential of our method of detecting the CPs in ECG.

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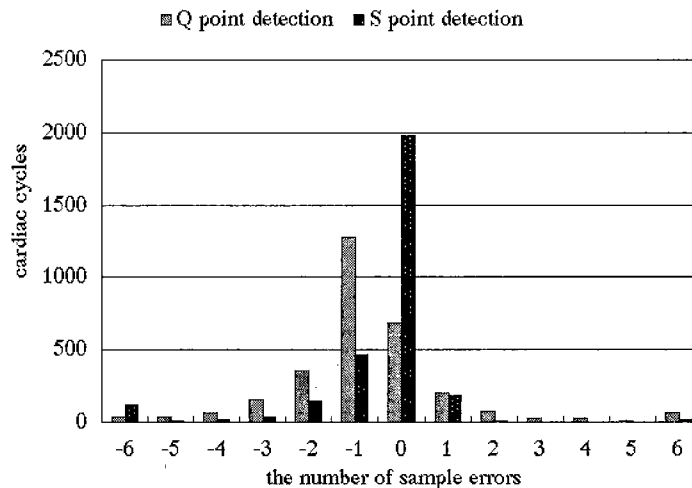
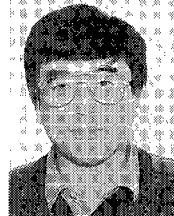


Fig. 6. The results of the CPs detection. Detection error is represented with the number of sampling. Since the ECG is digitized with sampling rate of 360 Hz, one sampling is 2.78 ms.

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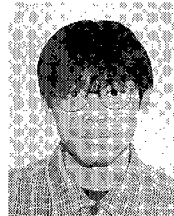
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